Received: 20 May 2023 | Accepted: 24 May 2023

DOI: 10.1111/2041-210X.14154

Methods in Ecology and Evolution

EDITORIAL

Active Remote Sensing for Ecology and Ecosystem Conservation

Towards complex applications of active remote sensing for ecology and conservation

Hooman Latifi[1,2] | Ruben Valbuena[3] | Carlos Alberto Silva[4]

[1]Department of Photogrammetry and Remote Sensing, Faculty of Geodesy and Geomatics Engineering, K. N. Toosi University of Technology, Tehran, Iran

[2]Department of Remote Sensing, University of Würzburg, Würzburg, Germany

[3]Forest Remote Sensing Division, Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden

[4]Forest Biometrics, Remote Sensing and Artificial Intelligence Lab (Silva Lab)—School of Forest Resources and Conservation, University of Florida, Gainesville, Florida, USA

Correspondence
Hooman Latifi
Email: hooman.latifi@kntu.ac.ir

Handling Editor: Aaron Ellison

Abstract

1. Remote sensing (RS) and geospatial sciences already amount to a long history of fostering research in topics related to ecology. Data and methods have mainly been subject to research and experiments, but trends are now emerging that suggest the use of RS in practical applications like nationwide monitoring programs and assisting global conservation goals. However, use of active remote sensing for ecological and conservation is in its infancy, and the implications of active sensor data, including light detection and ranging and radio detection and ranging that mostly deliver three-dimensional (3D) information, are still relatively primitive and have largely been limited to indirect use of their extracted proxies for ecological modelling.
2. This cross-journal special feature between *Methods in Ecology and Evolution*, *Journal of Animal Ecology*, *Journal of Applied Ecology* and *Journal of Ecology* includes 18 papers that include full research papers, reviews and technical applications. They are mostly novel in either or both their interpretation of proxies derived from active RS data and the direct usage of 3D RS techniques (terrestrial, airborne, UAV borne and spaceborne) to address ecological topics.
3. We categorized the published contributions into the following thematic groups, with some degree of overlap: (i) ecosystem structural analysis by active data (nine studies); (ii) response of animal populations to climate dynamics as shown by active data; (iii) interactive effects of forest structure and wildlife monitoring (five studies); (iv) forest inventories assisted by active data (one study) and (v) tree type classification by active data (one study).
4. *Synthesis*. The studies in this Special Feature and trends shown by other recent works at the interface of ecology and active RS confirm the ongoing shift from indirect and solely proxy-based approaches to direct and more data-science driven methods in approaching ecology and conservation problems by means of active sensors. Relatively affordable and accessible drone and citizen science-based on-demand active RS data acquisition are becoming common practice, and the future of sensor development is hypothesized to go beyond the current domination of very high spatial resolution data and towards multiple spaceborne platforms. These tools and methods will support spatial upscaling, uncertainty analysis, large-scale

mapping and monitoring of wildlife dynamics, among other topics that can take advantage of multitemporal/time series data. Nevertheless, access to demanding and costly very high-resolution data sources may still be maintained and optimized by establishing international and public–private partnered data pools.

KEYWORDS
active remote sensing, conservation, ecology, ecosystem structure, LiDAR, RADAR, UAV

1 | INTRODUCTION

1.1 | Background

When working on this Editorial, one of its authors tried the artificial intelligence (AI)-supported Bing® search engine (recently powered by Generative Pre-trained Transformer-4, GPT-4) by searching '*the current trends in remote sensing applications for ecology and ecosystem conservation*'. The results could be summarized briefly as the use of remote sensing data to monitor (1) biodiversity and ecosystem health, (2) land use and land cover changes, (3) climate change impacts on ecosystems, (4) invasive species, (5) wildlife populations and (6) water quality and quantity. The subsequent short chat with the standalone OpenAI-developed chatbot sought the current AI perception by listing a set of current trends comprising (1) integration of multi-source data, (2) advances in applying high-resolution imagery, (3) machine learning and AI, (4) unmanned aerial vehicle (UAV) applications and (5) citizen science, each accompanied with a short description on how the trends benefit from using remote sensing data and methods. A further supplementing of the test by adding '*active remote sensing*' only marginally added new useful details, including: (1) modelling ecological niches and habitats and (2) monitoring rewilding projects (via Bing® search engine). Iterating with the standalone chatbot resulted in a few sensor-related details like (1) LiDAR for ecosystem monitoring (vegetation structure, topography and biomass), (2) synthetic aperture radar (SAR) for land cover mapping, vegetation structure and growth, (3) echo sounding to study fish populations in aquatic ecosystems, and less-relevant applications like, (4) interferometric SAR (InSAR) for land deformation and subsidence and (5) microwave radiometry for soil moisture.

While these tests partly correspond with the general human perception within the remote sensing and ecology communities on existing trends, some additional fields seem to be under- or overlooked by both tools, giving a hint that there are 'applications' that have not yet evolved to 'trends' or perceptual 'trends' and are still at the level of limited applications. In this Editorial, we illustrate some examples of such trends that cannot be easily grasped from a quick AI analysis, and briefly discuss them alongside other more common trends in the application of active remote sensing in ecology and conversation.

2 | GENERAL AND SPECIFIC TRENDS

The Special Feature 'Active Remote Sensing for Ecology and Ecosystem Conservation' was conceptualized to showcase a part of state-of-the-art advances in the implications of Light Detection and Ranging (LiDAR) and Radio Detection and Ranging (RADAR) data and methods for science and practice in vegetation and wildlife ecology and conservation (summarized in Figure 1). It is jointly hosted by *Methods in Ecology and Evolution*, *Journal of Animal Ecology*, *Journal of Ecology* and *Journal of Applied Ecology* and is made up of 18 papers, including 15 original research articles, two reviews and one application (software paper). In the initial announcement of the Special Feature, the focal fields of active remote sensing data were deemed to comprise '*those dealing with forest management, conservation, and ecological processes as well as wildlife management, but also embrace particular applications like and modelling ecological niches and animal habitats through essential biodiversity variables (EBVs) as proxies*' (see https://besjournals.onlinelibrary.wiley.com/hub/active-remote-sensing). This statement was fully and excitingly supported by the range of papers submitted, and the published papers in the Special Feature. Of the accepted papers, four are published in *Journal of Animal Ecology*, two in *Journal of Applied Ecology*, four in *Journal of Ecology* and eight in *Methods in Ecology and Evolution*. When assessing the general trends being covered by the contributions, a few general (and partly overlapping) trends can be distinguished, including:

1. Stand-, canopy- and tree-level structural analysis by active RS data (Atkins et al., 2023; Blanchard et al., 2023; Boucher et al., 2023; Coverdale & Davies, 2023; Hardenbol et al., 2022; Schlund et al., 2022; Singh et al., 2023; Tatsumi et al., 2022; Zhang & Liu, 2023).
2. Climate-mediated response of animal populations (from insects to ungulates) as investigated by active RS data (Brlík et al., 2022; Hockridge et al., 2022).
3. At the interface of forest structure and wildlife monitoring (Davison et al., 2023; Lee et al., 2023; Petersen et al., 2023; Yoh et al., 2023; Zong et al., 2022).
4. Active data for forest inventory (Knott et al., 2023).
5. Tree type mapping by active remote sensing data (Allen et al., 2022).

However, the above grouping can be regarded as somewhat fuzzy, as multiple studies could potentially be grouped into more than one category. Examples are the smartphone application developed by Tatsumi et al. (2022) for 3D structural measurements, which could also be regarded as a tool for forest inventory, or the tree species mapping by Allen et al. (2022), which could also be

FIGURE 1 Schematic representation of active remote sensing applications for ecology and conservation. The items include: (1) satellite navigation on the medium earth orbit (MEO) as the main backbone of the well-established animal telemetry as well as all terrestrial, airborne and spaceborne earth observation, which is currently operated by constellations from global navigation satellite systems (GNSS); (2) the international space station (ISS) integrating the global ecosystem dynamics investigation (GEDI) as an example of spaceborne laser scanning system; (3) airborne laser scanning by piloted aircrafts; (4) terrestrial laser scanning; (5) Sentinel-1 satellite as an example of spaceborne synthetic aperture RADAR systems; and (6) a DJI Matrice-300 RTK with a Zenmuse L1 LiDAR payload as an example of an unmanned aerial vehicle (UAV)-based laser scanning system.

grouped in forest structural studies. Research within each of these groups also engages with the use of disparate data, methods and research questions. Similarly, multiple groups potentially can be merged into one broader category. The examples are '...forest inventory', 'tree type mapping...' and '...structural analysis' groups, which could potentially be merged. The same applies for 'climate-mediated response of animal populations...' and '...forest structure and wildlife monitoring'.

Along with the general trends described, specific trends were observed in the published contributions that show an emerging transition from rather indirect and solely proxy-based usage of active remote sensing derivatives towards more complex applications, that is, direct estimation of ecological metrics at multiple spatial scales, as was envisioned by Almeida et al. (2019), Latifi and Valbuena (2019) and Valbuena et al. (2020). We posit this to be driven by the constantly increasing accessibility and reduced cost-performance ratio of active data sources from terrestrial to spaceborne platforms. We show this transition with two examples below:

1. A shift in textbooks from focusing on passive to active remote sensing. Along with introducing the context of ecology and conservation (e.g. land cover/land use, vegetation, aquatic and coastal ecosystems, disturbances, landscape fragmentation, biodiversity), well-known textbooks on remote sensing for ecology and ecosystem conservation (e.g. Horning et al., 2010; Pettorelli, 2013) based their examples and conclusions on the use of passive, spaceborne remote sensing data (see also Wegmann et al., 2016). In contrast, more recently published textbooks have increasingly shifted from optical passive data processing towards either active data sources like LiDAR (Guo et al., 2023) or UAVs that are mostly known for carrying active/passive 3D sensors (Wich & Koh, 2018).
2. Active remote sensing proxies (e.g. coherency of SAR data and height/intensity percentiles from LiDAR) have been increasingly employed to indirectly model or classify ecological entities like wildlife niches (e.g. Hagar et al., 2020) and ecosystem structure for habitat suitability or wildlife species diversity (e.g. Bae et al., 2019; Kortmann et al., 2018). For airborne laser scanning data there is a clear trend from mainly technical applications in forestry practice (Maltamo et al., 2014) towards its use in attaining essential understanding of forest ecosystem functioning on scales never available before. The indirect, proxy-based methods for use in ecology and conservation practice were thoroughly reviewed by Simonson et al. (2014). However, the ongoing shift from indirect (implying less complex data processing) to direct (implying complex data processing) application, presented initially in the context of 3D remote sensing by Almeida et al. (2019), Latifi and Valbuena (2019), and Valbuena et al. (2020), is illustrated in the articles in this Special Feature. Examples include mutual effects of vegetation structure and fauna (Coverdale & Davies, 2023), wildfire disturbances and their interaction with habitat structure (Singh et al., 2023), and optimizing sample size or sampling grids for measurement of reference ecological data (Knott et al., 2023). Indeed, almost all the themes previously mentioned by Latifi and Valbuena (2019) as shaping the future research of 3D remote sensing (the majority of which being active data sources) were among the submissions to this cross-journal Special Feature.

The geographical distribution of the studies is presented in Figure 2. Figure 3 summarizes the keywords of the entire studies in a word cloud.

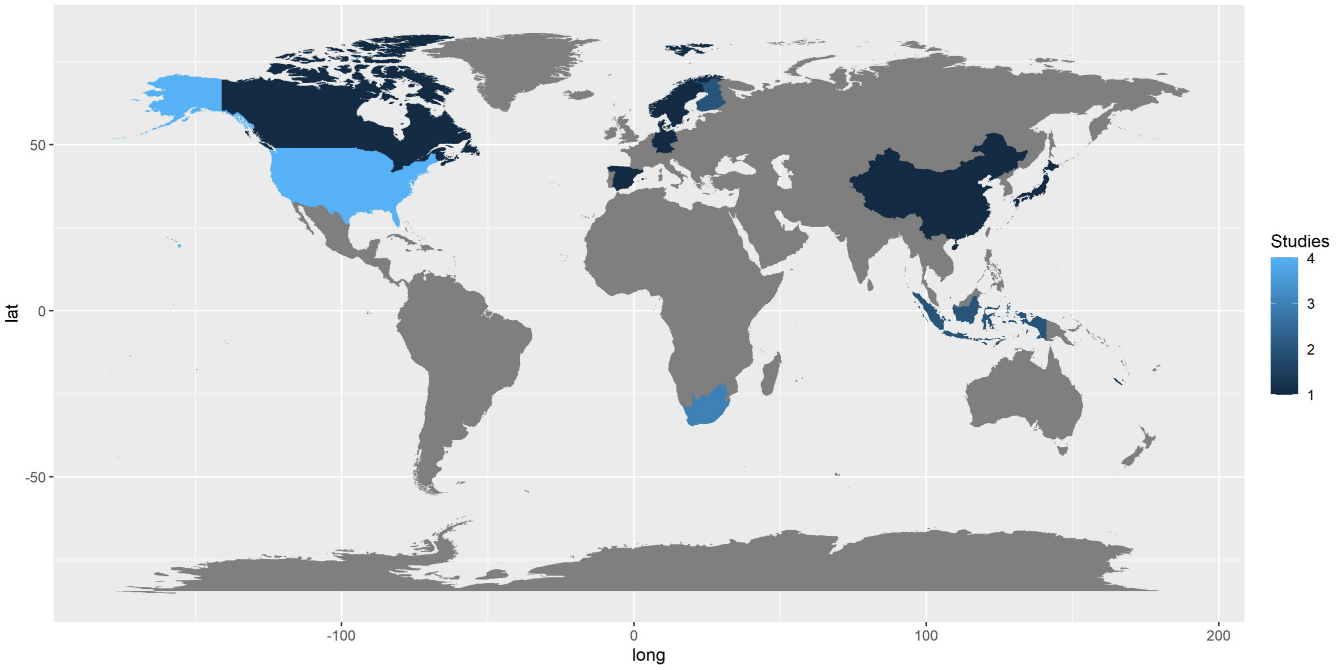

FIGURE 2 Geographical distribution of the sites in which the studies were carried out. Two studies are not included since they either encompassed large cross-country regions (Brlík et al., 2022) or were conceptual reviews with no geographical region (Coverdale & Davies, 2023).

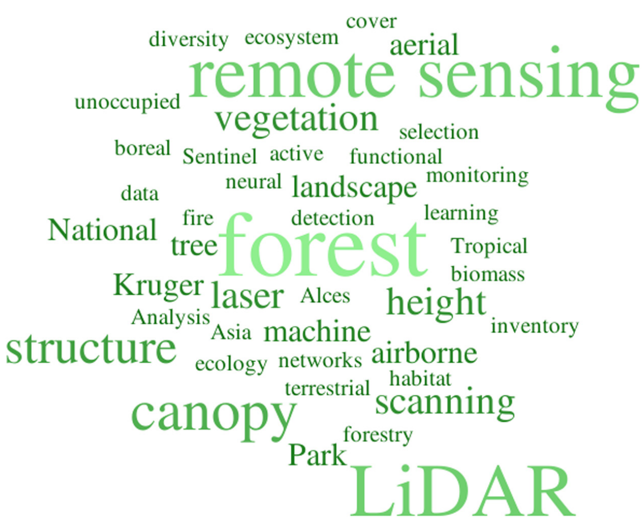

FIGURE 3 A word cloud of the most frequent terms from total 164 keywords of the 18 contributions. It includes words that have been repeated at least twice.

3 | THEMATIC GROUPS BEING COVERED IN THE SF

3.1 | Stand-, canopy- and tree-level structural analysis using active RS data

Vegetation structure and structural attributes are important ecological indicators and are listed among the essential biodiversity variables (EBVs) (Skidmore et al., 2021; Valbuena et al., 2020). Although encompassing a diverse range of variables, their remote sensing derivations literally refer to proxies that represent horizontal or vertical distribution of vegetation elements (or their combination, known as structural complexity), and more particularly for allometric variables like tree height, standing volume, aboveground biomass and crown size, which individually or jointly relate to other ecological phenomena. Terrestrial platforms to collect active data are apparently the most on-demand and flexible sources, but are still constrained by the spatial scale of their operation and can only be used over small sample plots or at single tree level. New LiDAR sensors integrated in Apple® smartphones provide low point densities of ca. 7 points/m^2 at closer distances to the targeted object, which can only reach few metres, in contrast to the very high point densities produced by tripod-mounted terrestrial laser scanners (TLS) that can reach ca. 150 points/m^2 at distances around 2.5 m and still reach much further distances (Luetzenburg et al., 2021). LiDAR sensors included in smartphones nonetheless provide an unparalleled operational versatility. Tatsumi et al. (2022) addressed the issue of the general dearth of free mobile applications for tree measurements using iPhone and iPad LiDAR sensors and introduced ForestScanner. The app reliable enables measuring of stem diameters and spatial coordinates of single trees. Although such built-in laser scanners are effective at reducing labour, time and financial costs required for tree measurements at small scale, and in particular by nonexperts (e.g. citizen scientists), their current applicability still seems to be limited to trunk-related measurements because the range of an iPhone LiDAR is very short (max. 5 m). Recent tests of ForestScanner under various broadleaf tree structural circumstances, that is, single- or multi-stem, coppice or high, showed very limited ability to capture crown details. In general, applications are constrained to environments containing only neat large trunks.

Among the nonterrestrial active remote sensing tools, state-or-the-art UAV-borne active payloads now enable capturing up to >1000 points/m^2 point densities, which is on the way to being effectively used for ecological applications like restoration (see novel insights in Robinson et al., 2022). Blanchard et al. (2023) applied UAV-borne laser scanner data to relate edge effects to forest structure, composition, function and microclimate, and showed correlations between distance to forest edge and canopy structure. They also showed how UAV-LiDAR could help in predicting a range of microclimate, biomass and taxonomic and functional properties at very high spatial resolutions and relate them to the mediatory effect of forest edges, derived vertical structural attributes and related them to height and fractional cover.

In savannas, Boucher et al. (2023) compared multiple UAV-LiDAR point clouds sampled at various flight altitudes and patterns and suggested flight altitude to be of greater effect than flight pattern on the derived savanna structural metrics. Although the effect size and direction were shown to be functions of vegetation type, flying at higher altitudes was suggested as a trade-off when sampling structural attributes for practical ecological applications across savanna ecosystems.

In a broader context, Coverdale and Davies (2023) reviewed the association between plant diversity and structural complexity as analysed by LiDAR and RADAR data sources. By testing the hypothesis of whether more diverse plant communities tend to be more structurally complex (a common belief, see Walter et al., 2021) in an active remote sensing context, Coverdale and Davies showed strong evidence of this relationship to be either linear or saturating, rather than exponential or negative. However, the relatively small number of available remote sensing studies on this topic points to the need for further complementary studies on both new sensors and data, and within a wider range of ecosystem types, to answer questions on the direction of this relationship and whether conservation-related actions like community restoration could drive structural complexity. Because the global development of ecosystem structure EBVs (Valbuena et al., 2020) is currently being operationalized, we recommend that this research line should be invested in as a priority in the coming years and shed more light on the relationships between ecosystem structure and biodiversity. Parallel to testing such fundamental ecological hypotheses, efforts have also been moving towards directly deriving required metrics from active data sources, which can potentially be further applied as inputs for a wide range of studies in ecology and conservation. In this Special Feature, Hardenbol et al. (2022) discuss how combining airborne active LiDAR and passive multispectral data can help in detecting retention trees, an important component for safeguarding biodiversity of fauna and flora in close-to-nature forestry (e.g. Fedrowitz et al., 2014). This can be of practical value in, for example, Nordic Europe, with country-wide aerial data regularly acquired by forest services. Hardenbol et al. (2022) achieved detection rates ranging from 41.7% (dead trees) to 83.8% (living trees) by applying an individual tree detection algorithm, although higher omission errors occurred for dead trees with smaller diameters and heights. However, adding spectral metrics from colour infrared photography did not systematically enhance the overall accuracies of classifying living conifers, living broadleaves or dead trees, indicating that the sole use of LiDAR metrics may suffice for separating retention trees from other trees. In a more general context for operational LiDAR-assisted forest inventories, Atkins et al. (2023) discussed the crucial issue of spatial resolution (grain and extent) over which structural metrics are derived from airborne LiDAR and how spatial scale might affect their derivation across a wide range of forest ecosystem types. The study suggested, however, that multiple spatial grain sizes may suffice for capturing the optimal scale (shown as the representative elementary area) of specific groups of forest metrics. For example, a spatial grain between 25 and 75 m was optimal for deriving canopy cover, canopy arrangement, canopy leaf area and canopy complexity, whereas canopy height metrics can best be captured by a grain size between 30 and 150 m.

Apart from solely using LiDAR data, its fusion with other active remote sensing data has led to the development of new techniques for the analysis of ecosystem structure (Valbuena et al., 2020), particularly since the recent advent of spaceborne LiDAR. While the launch of ICESat series started in 2003, it was only from 2018 that spaceborne LiDAR—through the NASA's Global Ecosystem Dynamics Investigation (GEDI) and ICESat-2 missions—has become operational for ecology and conservation. Inter alia, the photon-counting, large footprint and transect pattern for data acquisition has offered precious sources of 3D information, though often insufficient for spatially explicit and consistent estimates or upscaling over large areas. Spaceborne RADAR data offer a complementary source of data, particularly across the tropics. Schlund et al. (2022) suggested an approach to combine GEDI data with TanDEM-X polarimetric SAR data via a semi-empirical model for canopy height estimations over tropical forests and then validated the results with airborne LiDAR data. A higher and denser vegetation cover was shown to result in larger errors in the estimation of canopy height by the applied linear models. However, SAR-based approaches are generally expected to produce relatively large errors in canopy height estimations (here the minimum RMSE of 37.5%), which are still somewhat inevitable due to their status as the only sources of 3D data for deriving wall-to-wall vegetation structural metrics across tropical landscapes. The Special Feature also includes a related study by Zhang and Liu (2023), who applied ICESat-2 Advanced Topographic Laser Altimeter System (ATLAS) spaceborne LiDAR data to estimate forest height across boreal ecosystems. Their survey predominantly focused on detailing the common uncertainty problem of photon-counting LiDAR by means of Cook's Distance, a quality-control approach that was shown to be effective in cleaning the data and improving its correlation with airborne LiDAR data, thereby enhancing the applicability of ICESat-2 data for structural analysis of boreal vegetation.

Another important research line is on the study of how ecosystem disturbances affect vegetation structure (Bowd et al., 2021);

LiDAR has already been shown to provide useful proxies to show these effects (Gough et al., 2022). This also applies for fire, in both the forms of wildfire and prescribed burning. Singh et al. (2023) took long-term fixed fire regimes across savanna ecosystems as an example and showed how LiDAR data help with understanding the effects of fire exclusion and experimental burns in 1–6-year intervals. Fire season was shown to be the most influential factor on aboveground biomass, where fire occurrences during dry season burn more biomass than those during wet season, regardless of the savanna type. This effect was shown to be followed by fire frequency, but only across mesic savannas.

3.2 | Active remote sensing to assess climate-mediated response of animal populations

Thermal stress induced by climatic changes recently has been reported to undermine animal populations and increase their risk of extinction (e.g. Duffy et al., 2022; Sergio et al., 2018). Earlier remote sensing studies have largely focused on vegetation proxies extracted from optical multispectral data (e.g. Pettorelli et al., 2005), whereas subsequent studies generally suggested active sources like LiDAR for relevant tasks like discriminating between human infrastructure and vegetation, or deriving terrain topography and vertical and horizontal ecosystem structure to characterize animal habitats, which was still associated with limited accessibility for multitemporal studies like those related to animal movement (Neumann et al., 2015). This accessibility has been extensively increased with the launch of new spaceborne LiDAR devices of ICESat-2 and GEDI, and it is expected to increase after the launch of Multi-Footprint Observation LIDAR and Imager (MOLI) in 2024. As for SAR sensors, the launch of the C-band sensor on board the Sentinel-1 platform has offered tremendously high amount of data for wildlife monitoring applications that can also be directly processed via the Google Earth Engine platform.

This Special Feature showcased two rather advanced applications. In the first study, Brlík et al. (2022) followed the tactic of using stable isotopes for animal tracking (see Hobson & Wassenaar, 2019) but applied sulphur ($\delta^{34}S$) because of its broader longitudinal coverage across sub-Saharan Africa. Applying a range of environmental covariates (including active remote sensing-derived terrain elevation at 0.8 km spatial resolution) resulted in robust models linking migratory patterns and climatic variability across large scales. In the second study, Hockridge et al. (2022) examined whether varied fire regimes over long terms affect mound-building termites across south African savannas where the size and spatial distribution of the studied termite mounds were estimated by UAV-LiDAR. Despite being partly mediated by the site characteristics (nutrients and humidity), they showed that the size and distribution of the mounds were largely unaffected by fire seasonality and frequency, indicating that the ecosystem services from termite populations are expected to be also unaffected.

3.3 | Active remote sensing-derived ecosystem structure for wildlife monitoring

Information on forest structure provides useful inputs for monitoring wildlife populations (Helmisaari, 2000) as it helps with deriving proxies on, for example, ecosystem health, biomass and leaf traits that are related to wildlife presence and abundance (see Pardini et al., 2005 for an example on mammal species). Well-known LiDAR metrics like canopy cover and height distribution have been widely used to monitor habitat suitability (Guo et al., 2023). Wildlife presence as affected by forest structure changes has also been investigated by LiDAR (Lechner et al., 2020). In the collection presented here, active remote sensing was shown to enable supporting diverse ways to monitor wildlife. Zong et al. (2022) surveyed how visibility within temperate forest ecosystems, as characterized by combining terrestrial and airborne LiDAR, and suggested that at fine spatial scales, intermediate visibility is preferred by red deer *Cervus elaphus* for their summer habitat selection. The cumulative viewshed provided by the 3D LiDAR beams revealed not only the level of preferred visibility, but also a significant difference between preferred visibilities during day and night/twilight. A related study by Petersen et al. (2023) showed how metrics extracted from airborne LiDAR-related fine-scale forest structure to moose *Alces alces* in a boreal biome and helped test the hypothesis that biomass, canopy height and vertical complexity were all negatively correlated with the presence of moose. The thorough analysis additionally comprised examining whether the impacts vary with a set of climatic and disturbance-related factors and suggested largely uniform responses across multiple test sites distributed over the boreal biome. This fundamental result supports upscaling the moose responses from fine to coarse scales.

Habitat suitability, movement ecology and diversity of birds also can be described by habitat structural metrics derived from active remote sensing. Davison et al. (2023) suggested a robust correlation between habitat availability and bird assemblage composition. In the context of active data, they reported the equivalent importance of vegetation structure and habitat availability to describe patterns of bird richness across Denmark by combining land cover maps, structured citizen science data and LiDAR point clouds. The effect of anthropogenic activities on wildlife was also shown by Yoh et al. (2023), who used passive acoustic detectors and metrics from airborne LiDAR to show the effects of logging activities on tropical native and planted forests. Their results suggested different responses of groups of bat species to logging intensities and the resulting forest disturbances, which provided another complex ecological use case for active 3D data. Lastly, Lee et al. (2023) combined aerial photography and airborne LiDAR in structural models to study the effects of fire history and topography on taxonomic and functional diversities of ant assemblages. Both effects were supported, and LiDAR-derived vegetation structure was also shown to be correlated with individual ant traits. Functional and taxonomic diversities of insect populations were also associated with interactive effects of topography, vegetation structure and disturbance.

3.4 | Forest inventory assisted by active data

Promoting active remote sensing data, in particular airborne laser scanning, for forest inventory and analysis dates has been used for just over 20 years (Dubayah & Drake, 2000) and has already been well-established as an effective tool to be integrated into landscape-, regional- and occasionally national-level inventory of forest allometric attributes. However, the presence of outliers resulting from remote sensing data processing can reduce the signal-to-noise ratio, affecting both the mean and standard deviation of the predicted and spatially upscaled forest attributes (e.g. Li et al., 2022). The major sources for the presence of outliers include purely statistical outliers, those related to sampling, and temporal and spatial mismatches between field and remote sensing data (Knott et al., 2023). Knott et al. (2023) thoroughly reviewed this issue for aboveground biomass estimation from the US national forest inventory and stated that inclusion or exclusion of outliers may result in different estimates of mean and standard error of forest biomass.

3.5 | Active remote sensing to support tree species mapping

Accurate tree species classification and mapping is improving because of increased availability of multiple remote sensing data, including LiDAR and RADAR sources (Fassnacht et al., 2016). Fassnacht et al. (2016) broadly categorized the applications by remote sensing data source, classification method and spatial level, whereas Michałowska and Rapiński (2021) focused more specifically on airborne LiDAR data, and concluded that the effectiveness of using full-waveform extracted metrics along with height metrics and machine learning classification could improve the accuracy of tree species mapping. However, state-of-the-art and more complex methods like deep learning that enable considering numerous geometric 3D features are still rarely presented in the literature. Allen et al. (2022) tested these methods using terrestrial laser scanning data from a Mediterranean test site and reported that combining deep learning architecture and TLS 3D point clouds reduced manual labelling of single tree stems and solved the problem of individual species identification that occurs when using TLS data. However, further research is also needed to test deep learning methods on multi-stem trees or coppice structures across arid and semi-arid ecosystems, as they add to the existing complication of using dense 3D point clouds for species classification at single tree levels.

4 | CONCLUSIONS AND THE WAY FORWARD

Ecological and conservation implications of active remote sensing data are rapidly evolving from experimental to operational domains. The trends and thematic groups covered in this Special Feature are diverse but are united by their focus on ecosystem structure. Active sensors are and will remain for the foreseeable future the main source of 3D information to characterize mainly the vertical, but also the horizontal, structure of any ecosystem (Valbuena et al., 2020). The current spaceborne active sensor missions will presumably expand in the near future with the launching and continuation of multiple LiDAR (e.g. JAXA's MOLI) and RADAR (e.g. NASA-ISRO NISAR) missions, suggesting expansion of large-scale applications that can enhance our understanding of the relationships between ecosystem structure and function and help set conservation priorities worldwide. In the meantime, ecological and conservation applications at finer spatial scales also can be effectively supported by the data and knowledge provided by ecological remote sensing data pools (Latifi et al., 2021).

AUTHOR CONTRIBUTIONS

Hooman Latifi wrote the initial draft of this manuscript and provided and analytical figures. Ruben Valbuena and Carlos Alberto Silva revised the initial manuscript and added material to the revised draft. All authors finalized the manuscript.

ACKNOWLEDGEMENTS

The guest editors of this SF thank all the efforts by the international authors, reviewers, editorial boards and editorial offices of the four participating BES journals (*Methods. Ecol. Evol.*, *J. Ecol.*, *J. Appl. Ecol.* and *J. Anim. Ecol.*), without which this collection would not have been materialized within the last nearly 2 years. We appreciate Seyed Arvin Fakhri for his great support for providing the Figure 1 of this paper. The work done by the H.L. was within the research laboratory 'Remote Sensing for Ecology and ecosystem conservation (RSEEC)' of the K. N. Toosi University of Technology (https://www.researchgate.net/lab/Research-Lab-Remote-Sensing-for-Ecology-and-Ecosystem-Conservation-RSEEC-Hooman-Latifi).

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest among the authors.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/2041-210X.14154.

DATA AVAILABILITY STATEMENT

There is no data used in this article.

ORCID

Hooman Latifi https://orcid.org/0000-0003-1054-889X
Ruben Valbuena https://orcid.org/0000-0003-0493-7581

REFERENCES

Allen, M. J., Grieve, S. W. D., Owen, H. J. F., & Lines, E. R. (2022). Tree species classification from complex laser scanning data in Mediterranean forests using deep learning. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.13981

Almeida, D. R. A., Stark, S. C., Valbuena, R., Broadbent, E. N., Silva, T. S. F., Resende, A. F., Ferreira, M. P., Cardil, A., Silva, C. A., Amazonas, N., Zambrano, A. M., & Brancalion, P. H. (2019). A new era in Forest restoration monitoring. *Restoration Ecology*, *28*, 8–11. https://doi.org/10.1111/rec.13067

Atkins, J. W., Costanza, J., Dahlin, K. M., Dannenberg, M. P., Elmore, A. J., Fitzpatrick, M. C., Hakkenberg, C. R., Hardiman, B. S., Kamoske, A., LaRue, E. A., Silva, C. A., Stovall, A. E. L., & Tielens, E. K. (2023). Scale dependency of lidar-derived forest structural diversity. *Methods in Ecology and Evolution*, *14*, 708–723. https://doi.org/10.1111/2041-210X.14040

Bae, S., Levick, S. R., Heidrich, L., Magdon, P., Leutner, B. F., Wöllauer, S., Serebryanyk, A., Nauss, T., Krzystek, P., Gossner, M. M., Schall, P., Heibl, C., Bässler, C., Doerfler, I., Schulze, E.-D., Krah, F.-S., Culmsee, H., Jung, K., Heurich, M., … Müller, J. (2019). Radar vision in the mapping of forest biodiversity from space. *Nature Communications*, *10*, 4757. https://doi.org/10.1038/s41467-019-12737-x

Blanchard, G., Barbier, N., Vielledent, G., Ibanez, T., Hequet, V., McCoy, S., & Birnbaum, P. (2023). UAV-lidar reveals that canopy structure mediates the influence of edge effects on forest diversity, function and microclimate. *Journal of Ecology*. https://doi.org/10.1111/1365-2745.14105

Boucher, P., Hockridge, E. G., Singh, J., & Davies, A. B. (2023). Flying high: Sampling savanna vegetation with UAV-lidar. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.14081

Bowd, E., Blanchard, W., McBurney, L., & Lindenmayer, D. (2021). Direct and indirect disturbance impacts on forest biodiversity. *Ecosphere*, *12*(12), e03823. https://doi.org/10.1002/ecs2.3823

Brlík, B., Procházka, P., Hansson, B., Stricker, C. A., Yohannes, E., Powell, R. L., & Wunder, M. B. (2022). Animal tracing with sulfur isotopes: Spatial segregation and climate variability in Africa likely contribute to population trends of a migratory songbird. *The Journal of Animal Ecology*. https://doi.org/10.1111/1365-2656.13848

Coverdale, T. C., & Davies, A. B. (2023). Unravelling the relationship between plant diversity and vegetation structural complexity: A review and theoretical framework. *Journal of Ecology*. https://doi.org/10.1111/1365-2745.14068

Davison, C. W., Assmann, J. J., Normand, S., Rahbek, C., & Morueta-Holme, N. (2023). Vegetation structure from LiDAR explains the local richness of birds across Denmark. *Journal of Applied Ecology*, *29*, 39–50. https://doi.org/10.1111/ddi.13644

Dubayah, R. O., & Drake, J. B. (2000). Lidar remote sensing for forestry. *Journal of Forestry*, *98*(6), 44–46. https://doi.org/10.1093/jof/98.6.44

Duffy, K., Gouhier, T. C., & Ganguly, A. R. (2022). Climate-mediated shifts in temperature fluctuations promote extinction risk. *Nature Climate Change*, *12*, 1037–1044. https://doi.org/10.1038/s41558-022-01490-7

Fassnacht, F. E., Latifi, H., Stereńczak, K., Modzelewska, A., Lefsky, M., Waser, L., Straub, C., & Ghosh, A. (2016). Review of studies on tree species classification from remotely sensed data. *Remote Sensing of Environment*, *186*, 64–87. https://doi.org/10.1016/j.rse.2016.08.013

Fedrowitz, K., Koricheva, J., Baker, S. C., Lindenmayer, D. B., Palik, B., Rosenvald, R., Beese, W., Franklin, J. F., Kouki, J., Macdonald, E., Messier, C., Sverdrup-Thygeson, A., & Gustafsson, L. (2014). Can retention forestry help conserve biodiversity? A meta-analysis. *Journal of Applied Ecology*, *51*(6), 1669–1679. https://doi.org/10.1111/1365-2664.12289

Gough, C. M., Atkins, J. W., Fahey, R. T., Curtis, P. S., Bohrer, G., Hardiman, B. S., Hickey, L. J., Nave, L. E., Niedermaier, K. M., Clay, C., Tallant, J. M., & Bond-Lamberty, B. (2022). Disturbance has variable effects on the structural complexity of a temperate forest landscape. *Ecological Indicators*, *140*, 109004. https://doi.org/10.1016/j.ecolind.2022.109004

Guo, Q., Su, Y., & Hu, T. (2023). *LiDAR principles, processing and applications in forest*. Academic Press. ISBN: 9780128238943.

Hagar, J. C., Yost, A., & Haggerty, P. K. (2020). Incorporating LiDAR metrics into a structure-based habitat model for a canopy-dwelling species. *Remote Sensing of Environment*, *236*, 111499. https://doi.org/10.1016/j.rse.2019.111499

Hardenbol, A. A., Korhonen, L., Kukkonen, M., & Maltamo, M. (2022). Detection of standing retention trees in boreal forests with airborne laser scanning point clouds and multispectral imagery. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.13995

Helmisaari, H. S. (2000). Structure and functioning of forest ecosystems. In E. Mälkönen (Ed.), *Forest condition in a changing environment*. Forestry sciences (Vol. *65*). Springer. https://doi.org/10.1007/978-94-015-9373-1_21

Hobson, K. A., & Wassenaar, L. I. (2019). *Tracking animal migration with stable isotopes* (2nd ed.). Academic Press. ISBN: 978-0-12-814723-8.

Hockridge, E. G., Singh, J., Boucher, P. B., & Davies, A. B. (2022). Resistance of termite mounds to variation in long-term fire regimes across semi-arid African savannas. *The Journal of Animal Ecology*. https://doi.org/10.1111/1365-2656.13830

Horning, N., Robinson, J. A., Sterling, E. J., Turner, W., & Spector, S. (2010). *Remote sensing for ecology and conservation: A handbook of techniques*. Oxford University Press. ISBN: 9780199219940.

Knott, J. A., Liknes, G. C., Giebink, C. L., Oh, S., Domke, G. M., McRoberts, R. E., Quirino, V. F., & Walters, B. F. (2023). Effects of outliers on remote sensing-assisted forest biomass estimation: A case study from the United States national forest inventory. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.14084

Kortmann, M., Heurich, M., Latifi, H., Rösner, S., Seidl, R., Müller, J., & Thorn, S. (2018). Forest structure following natural disturbances and early succession provides habitat for two avian flagship species, capercaillie (*Tetrao urogallus*) and hazel grouse (*Tetrastes bonasia*). *Biological Conservation*, *226*, 81–91. https://doi.org/10.1016/j.biocon.2018.07.014

Latifi, H., Holzwarth, S., Skidmore, A., Bruna, J., Cervenka, J., Darvishzadeh, R., Hais, M., Heiden, U., Homolová, L., Krzystek, P., Schneider, T., Starý, M., Wang, T., Müller, J., & Heurich, M. (2021). A laboratory for conceiving essential biodiversity variables (EBVs)—The data pool initiative for the Bohemian forest ecosystem. *Methods in Ecology and Evolution*, *12*(11), 2073–2083. https://doi.org/10.1111/2041-210X.13695

Latifi, H., & Valbuena, R. (2019). Current trends in forest ecological applications of three-dimensional remote sensing: Transition from experimental to operational solutions? *Forests*, *10*(10), 891. https://doi.org/10.3390/f10100891

Lechner, A. M., Foody, G. M., & Boyd, D. S. (2020). Applications in remote sensing to forest ecology and management. *One Earth*, *2*(5), 405–412. https://doi.org/10.1016/j.oneear.2020.05.001

Lee, R. H., Kwong, I. H. Y., Tsang, T. P. M., Wong, M. K. L., & Guénard, B. (2023). Remotely sensed environmental data as ecological proxies for ground-dwelling ant diversity along a subtropical forest succession gradient. *Journal of Ecology*, In Press. https://doi.org/10.1111/1365-2745.14109

Li, Z., Bi, S., Hao, S., & Ciu, Y. (2022). Aboveground biomass estimation in forests with random forest and Monte Carlo-based uncertainty analysis. *Ecological Indicators*, *142*, 109246. https://doi.org/10.1016/j.ecolind.2022.109246

Luetzenburg, G., Kroon, A., & Bjørk, A. A. (2021). Evaluation of the Apple iPhone 12 Pro LiDAR for an application in geosciences. *Scientific Reports*, *11*, 22221. https://doi.org/10.1038/s41598-021-01763-9

Maltamo, M., Næsset, E., & Vauhkonen, J. (Eds.) (2014). *Forestry applications of airborne laser scanning – Concepts and case studies* (p. 484). Springer Science+Business Media Dordrecht. ISBN 978-94-017-8662-1.

Michałowska, M., & Rapiński, J. (2021). A review of tree species classification based on airborne LiDAR data and applied classifiers. *Remote Sensing*, *13*(3), 353. https://doi.org/10.3390/rs13030353

Neumann, W., Martinuzzi, S., Estes, A. B., Pedgeon, A. M., Dettki, H., Ericsson, G., & Radeloff, V. C. (2015). Opportunities for the application of advanced remotely-sensed data in ecological studies of terrestrial animal movement. *Movement Ecology*, *3*, 8. https://doi.org/10.1186/s40462-015-0036-7

Pardini, R., de Souza, S. M., Braga-Neto, R., & Metzger, J.-P. (2005). The role of forest structure, fragment size and corridors in maintaining small mammal abundance and diversity in an Atlantic forest landscape. *Biological Conservation*, *124*(2), 253–266. https://doi.org/10.1016/j.biocon.2005.01.033

Petersen, T. K., Kolstad, A. L., Kouki, J., Leroux, S. J., Potvin, L. R., Tremblay, J.-P., Wallgren, M., Widemo, F., Cromsigt, J. P. G. M., Courtois, C., Austrheim, G., Gosse, J., den Herder, M., Hermanutz, L., & Speed, J. D. M. (2023). Airborne laser scanning reveals uniform responses of forest structure to moose (*Alces alces*) across the boreal forest biome. *Journal of Ecology*. https://doi.org/10.1111/1365-2745.14093

Pettorelli, N. (2013). Proxy-based approaches in ecology and the importance of remote sensing. In *The normalized difference vegetation index*. Oxford University Press. ISBN: 9780199693160. https://doi.org/10.1093/acprof:osobl/9780199693160.003.0001

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J.-M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, *20*(9), 503–510. https://doi.org/10.1016/j.tree.2005.05.011

Robinson, J. M., Harrison, P. A., Mavoa, S., & Breed, M. F. (2022). Existing and emerging uses of drones in restoration ecology. *Methods in Ecology and Evolution*, *13*(9), 1899–1911. https://doi.org/10.1111/2041-210X.13912

Schlund, M., Wenzel, A., Camarretta, N., Stiegler, C., & Erasmi, S. (2022). Vegetation canopy height estimation in dynamic tropical landscapes with TanDEM-X supported by GEDI data. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.13933

Sergio, F., Blas, J., & Hiraldo, F. (2018). Animal responses to natural disturbance and climate extremes: A review. *Global and Planetary Change*, *161*, 28–40. https://doi.org/10.1016/j.gloplacha.2017.10.009

Simonson, W. D., Allen, H. D., & Coomes, D. A. (2014). Applications of airborne lidar for the assessment of animal species diversity. *Methods in Ecology and Evolution*, *5*(8), 719–729. https://doi.org/10.1111/2041-210X.12219

Singh, J., Boucher, P. B., Hockridge, E. G., & Davies, A. B. (2023). Effects of long-term fixed fire regimes on African savanna vegetation biomass, 1 vertical structure and tree stem density. *Journal of Applied Ecology*, In Press.

Skidmore, A. K., Coops, N. C., Neinavaz, E., Ali, A., Schaepman, M. E., Paganini, M., Kissling, W. D., Vihervaara, P., Darvishzadeh, R., Feilhauer, H., Fernandez, M., Fernández, N., Gorelick, N., Geijzendorffer, I., Heiden, U., Heurich, M., Hobern, D., Holzwarth, S., Muller-Karger, F. E., … Wingate, V. (2021). Priority list of biodiversity metrics to observe from space. *Nature Ecology & Evolution*, *5*, 896–906. https://doi.org/10.1038/s41559-021-01451-x

Tatsumi, S., Yamaguchi, K., & Furuya, N. (2022). ForestScanner: A mobile application for measuring and mapping trees with LiDAR-equipped iPhone and iPad. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.13900

Valbuena, R., O'Connor, B., Zellweger, F., Simonson, W., Vihervaara, P., Maltamo, M., Silva, C. A., Almeida, D. R. A., Danks, F., Morsdorf, F., Chirici, G., Lucas, R., Coomes, D. A., & Coops, N. C. (2020). Standardising ecosystem morphological traits from 3D information sources. *Trends in Ecology & Evolution*, *35*, 656–667. https://doi.org/10.1016/j.tree.2020.03.006

Walter, J. A., Stovall, A. E. L., & Atkins, J. W. (2021). Vegetation structural complexity and biodiversity in the Great Smoky Mountains. *Ecosphere*, *12*(3), e03390. https://doi.org/10.1002/ecs2.3390

Wegmann, M., Leutner, B., & Dech, S. (2016). *Remote sensing and GIS for ecologists*. Pelagic Publishing. ISBN: 97817884270223.

Wich, S. A., & Koh, L. P. (2018). *Conservation drones: Mapping and monitoring biodiversity*. Oxford University Press. ISBN: 9780198787617.

Yoh, N., Seaman, D. J., Deere, N. J., Bernadr, H., Bicknell, J. E., & Streubig, M. J. (2023). Benign effects of logging on aerial insectivorous bats in Southeast Asia revealed by remote sensing technologies. *Journal of Applied Ecology*. https://doi.org/10.1111/1365-2664.14398

Zhang, T., & Liu, D. (2023). Improving ICESat-2-based boreal forest height estimation by a multivariate sample quality control approach. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.14112

Zong, X., Wang, T., Skidmore, A. K., & Heurich, M. (2022). LiDAR reveals a preference for intermediate visibility by a forest-dwelling ungulate species. *The Journal of Animal Ecology*. https://doi.org/10.1111/1365-2656.13847

How to cite this article: Latifi, H., Valbuena, R., & Silva, C. A. (2023). Towards complex applications of active remote sensing for ecology and conservation. *Methods in Ecology and Evolution*, *14*, 1578–1586. https://doi.org/10.1111/2041-210X.14154